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The use of proactive risk management to reduce emergency service vehicle crashes among firefighters

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ABSTRACT

Introduction: Emergency service vehicle crashes (ESVCs), including rollovers and collisions with other vehicles and fixed objects, are a leading cause of death among U.S. firefighters. Risk management (RM) is a proactive intervention to identifying and mitigating occupational risks and hazards. The goal of this study was to assess the effect of RM in reducing ESVCs. *Methods:* Three fire departments (A, B and C), representing urban and suburban geographies, and serving medium to large populations, participated in facilitated RM programs to reduce their ESVCs. Interventions were chosen by each department to address their department-specific circumstances and highest risks. Monthly crash rates per 10,000 calls were calculated for each department an average of 28 months before and 23 months after the start of the RM programs. Interrupted time series analysis was used to assess the effect of the RM programs on monthly crash rates. Poisson regression was used to estimate the number of crashes avoided. Economic data from Department A were analyzed to estimate cost savings. *Results:* Department A had a 15.4% (P = 0.30) reduction in the overall monthly crash rate immediately post-RM and a 1% (P = 0.18) decline per month thereafter. The estimated two-year average cost savings due to 167 crashes avoided was $253,100 (95%CI= $192,355 – $313,885). Department B had a 9.7% (P = 0.70) increase in the overall monthly crash rate immediately post-RM and showed no significant changes in their monthly crash rate. Department C had a 28.4% (P = 0.001) reduction in overall monthly crash rate immediately post-RM and a 1.2% (P = 0.09) increase per month thereafter, with an estimated 122 crashes avoided. *Conclusions:* RM programs have the potential to reduce ESVCs in the fire service and their associated costs; results may vary based on the interventions chosen and how they are implemented. *Practical applications:* Risk management may be an effective and broadly implemented intervention to reduce ESVCs in the US fire service.

1. Introduction

1.1. Background/Rationale

Firefighting is a dangerous occupation with many fatalities and injuries (Haynes & Molis, 2017; Poplin, Harris, Pollack, Peate, & Burgess, 2012). Emergency service vehicle crashes (ESVCs) are a key cause of occupational fatalities and injuries, and are associated with significant economic costs (Fahy, 2008; Griffin et al., 2016; Maguire, Hunting, Smith, & Levick, 2002; United States Fire Administration, 2017). Between 1990 and 2016, there were over 400,000 ESVCs in the United States and nearly 30,000 associated

Abbreviations: RM, Risk Management; ESVC, emergency service vehicle crash; US, United States, 95; CI, 95 percent confidence interval.

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firefighter injuries while traveling to or from emergencies; the frequency of crashes has remained relatively unchanged since 1990 (Haynes & Molis, 2017). Data from the National Highway Transportation Safety Administration (NHTSA) indicate that the leading types of fatal ESVCs are rollovers or overturns (49%), collisions with other moving vehicles (20%), and collisions with trees/fixed objects (14%); the most common collisions were with moving vehicles (74%), parked vehicles (11%), and fixed objects (7%; Donoughe et al., 2012). ESVCs are not only dangerous for firefighters, but also pose a hazard to other public road users who are at significantly greater risk for fatality in these fatal crashes (Donoughe et al., 2012; Fahy, 2008). Between 2011 and 2015, NHTSA reported that civilians accounted for over 73% of the fatalities in all fatal ESVCs, including pedestrian and bicyclist casualties (Fahy, 2008; National Highway Traffic Safety Administration, 2017).

Proactive risk management (RM) is a cyclical process of identifying occupational risks and hazards, prioritizing them, and implementing interventions to mitigate high priority risks (International Organization for Standardization, 2009). RM may be applied in nearly any occupational setting and has been used to address occupational injury and mortality in fire department settings (Bui et al., 2017; Poplin et al., 2015). RM applied to physical activity-related injuries in the fire service was associated with significant reductions in injuries, worker compensation claims, and cost savings (Griffin et al., 2016). A recent systematic review found that RM used in the London Fire Brigade was effective in reducing ESVC rates over time (Bui et al., 2018). However, the effectiveness of RM may be different in the United States where government regulations are generally more prescriptive in nature (Burgess et al., 2014).

In general, fire departments are amenable to using RM for mitigating occupational risks and hazards, and the process may be widely and readily adopted in departments of varying size, composition (i.e., career and volunteer departments), and geography with minimal resources or technical expertise (Bui et al., 2017; Poplin et al., 2015). To date, there have been no rigorous evaluations of RM programs designed to reduce ESVCs in the United States. Formal evaluations of RM programs are necessary for informing health and safety officers of expected program effects and augmenting the evidence base for the use of RM in the fire service.

1.2. Objectives

The primary objective of this study was to evaluate the effectiveness of proactive RM programs in preventing ESVCs in the U. S. fire service. Our secondary objective was to estimate cost savings associated with reductions in ESVCs as a result of the RM program.

2. Materials and methods

2.1. Setting and participants

Three fire departments (herein named Departments A, B, and C) of varying sizes, serving urban and suburban geographies, participated in the study. Department C joined the study approximately one year after the other two departments. The three fire departments each completed a separate facilitated RM program and implemented a series of interventions tailored to their specific risks aimed at reducing ESVCs. Department A was a large career fire department in a dense urban environment. Department B was a county career combination fire department, serving a geographic area similar to Department A, but with a much smaller population served. Department C was a large career county fire department, serving a suburban population covering the largest geographic area of the three departments.

The full RM programs were described in a previously published report (Bui et al., 2017). In summary, an interdisciplinary RM team consisting of firefighters, officers, and senior administrators was formed at each department to participate in the RM process. The process took place over the course of 4–6 meetings at each department and was facilitated by the study authors. Crash data from each department were summarized and reviewed by the RM teams. The teams created a risk register of common crash types, risks and hazards, and prioritized each using a severity-by-frequency risk prioritization matrix (National Patient Safety Agency, 2008). The team catalogued controls and interventions that were currently in place for the high priority risks and hazards and identified additional interventions to adopt and implement.

Department A revised their Code 3 response policy and backing SOP, installed side and rearview cameras on a subset of ambulances, trained driver trainers, and increased the frequency of remedial driver training. Department B updated their driver training curriculum based on crash trends on a quarterly basis, mapped out locations of recent deer collisions, and distributed the maps to stations to raise awareness of high risk areas, instituted standardized training for bay door operations, and installed telematics units on 12 apparatus to identify high risk driving behaviors. Department C implemented an enhanced driver training program, featuring both classroom and hands on "rodeo" cone course training, installed telematics units on 31 engines to monitor driver behaviors, and used the collected telematics data in training and coaching sessions with drivers.

2.2. Data sources/measurements

Crash data from administrative databases were submitted by each department for analysis. The datasets included crash records for crashes involving all fire department apparatus. Records are generated by reports submitted by firefighters and officers each time a crash occurs that results in damage to a department apparatus and/or to a civilian vehicle or property. Each department has an SOP in place for timely reporting of vehicle crashes. In some cases, police reports are submitted and attached to the crash records when available. While there were variations in each database, all databases included at least an assigned unique record identifier, incident date, and narrative describing the circumstances of the crash.

Each department also provided emergency fire service call volumes from their respective dispatch offices. Emergency call volumes were used as a measure of at-risk exposure and used to calculate crash rates at each department. Department A reported "run volume," which is a count of apparatus responding to each emergency call. This was used as an approximation for call volume in Department A.

Cost data were obtained for Department A and used to estimate average ESVC costs. Cost data for Departments B and C either were not available due to specifics of fire department appropriations/departmental accounting or were considered sensitive and could not be released. The cost data obtained from Department A included the direct vehicle repair costs and tort claims for ESVCs occurring between 2013–2014. The average ESVC cost was used to estimate cost savings in Department A using the statistical methods described below and adjusted to 2018 dollars.

2.3. Variables

The primary outcome of interest was department vehicle crashes. The administrative crash databases were reviewed to ensure all road crashes were included. Any crash involving a heavy apparatus, such as an engine, aerial truck, or ambulance was included. Lightweight passenger vehicles and trucks, such as officer or chief vehicles, were also included in the analysis. Crashes involving non-road apparatus and equipment that were outside of the scope of the RM program were excluded (e.g., boats, golf carts).

In addition to all crashes, we assessed the effectiveness of the RM programs on two sub-types of crashes, Code 3 responses in Department A and preventable crashes in Department C. Department A's crash records included an indicator variable to signify if a vehicle was on a Code 3 response with lights and sirens activated at the time of the crash. Since Department A implemented a policy intervention to reduce the use of lights and sirens, we expected to observe a reduction in their Code 3 crash rates. Department C's crash review panel regularly reviews all crashes involving department apparatus and adjudicates preventability of each crash. Crashes are deemed preventable if the incident could have been avoided had the driver taken some reasonable action or the crash was determined to be caused by the driver's actions. For example, if the driver was speeding and failed to yield at a red light and struck a civilian vehicle. A crash is deemed non-preventable if a driver could not have reasonably avoided the crash. For example, if an apparatus is stopped at a red light and is rear ended by a civilian vehicle. Since the primary intervention implemented at Department C was driver training, this sub-analysis was motivated by the hypothesis that enhanced driver training would have a direct effect on preventable crashes through improvements to driver skills/behaviors.

Monthly crash rates were calculated by dividing the total number of crashes by the total number of emergency service calls for the corresponding month and multiplied by 10,000 to obtain a standard rate of crashes per 10,000 calls. Since only quarterly emergency service call volume for Department C was available, the call totals were divided by three to approximate monthly volume for the department. A Code 3 crash rate was calculated for Department A and a preventable crash rate for Department C.

2.4. Statistical methods

Interrupted time series analysis was used to evaluate the longitudinal effect of the RM program on ESVCs at each department (Bernal, Cummins, & Gasparrini, 2017; Linden, 2015). The monthly crash rate time series was modeled as:

$$Y_t = \beta_0 + \beta_1 \mathrm{T}_t + \beta_2 X_t + \beta_3 X_t \mathrm{T}_t + \in_t,$$

where Y_t is the monthly crash rate at month t, T_t is the continuous time (in months) since the start of the study observation period, X_t is a binary indicator variable representing the intervention (X_t=0 during pre-RM and X_t = 1 during post-RM period), and $X_t\mathrm{T}_t$ is an interaction term.

In this model, β_0 estimates the baseline crash rate at month zero (i.e., rate at beginning of time series); β_1 is the average change in monthly crash rate before the RM program is completed; β_2 estimates the level change in the monthly crash rate immediately after the RM program is completed; β_3 is the average change in the monthly crash rate post-RM; and $\in_t$ is an error term representing random variability not explained by the model.

The monthly crash rate time series for all crashes was modeled for each department. Sub-analyses were also done for 'Code 3' (i.e., lights and siren on) crashes at Department A and 'preventable' crashes at Department C. If the RM program was effective, we would expect significant ($P < 0.05$) and negative β_2 coefficients, indicating an immediate drop in monthly crash rates after the RM program was completed. Moreover, we would expect a significant and negative β_3 coefficient to indicate a sustained negative trend in the monthly crash rate post-RM.

Coefficients were estimated using ordinary least squares regression. To account for residual autocorrelation and heteroscedasticity in time series data, Newey-West standard errors were estimated with the specified appropriate lag order of autocorrelation for each department time series (Hardin, 1998; Newey & West, 1987). Cumby-Huizinga general test for autocorrelation in time series was used to identify statistically significant lags in crash rate time series (Baum & Schaffer, 2015; Cumby & Huizinga, 1990). Ordinary least squares regression with Newey-West standard errors was also used to estimate the overall change in average monthly crash rates pre- and post-RM for each department.

Poisson regression models were used to estimate number of crashes expected during the study period, had the pre-RM crash trend continued at each department. We compared the expected crash counts to the actual number of crashes observed during the post-RM period to estimate the number of crashes avoided at each department. A sub analysis of the direct cost of repair and tort claims was performed for Department A. We calculated the average cost and 95% confidence interval per crash using all available repair cost data and tort claims costs. An estimate of the cost savings was determined by multiplying the average and 95% confidence interval of ESVC cost by the point estimate of crashes avoided at Department A during the post-RM follow-up period. Cost estimates were adjusted to reflect 2018 dollars.

3. Results

3.1. Descriptive and outcome data

Each department reported 51 months of crash data with an average of 28 months of data pre-RM and 23 months of data post-RM (Table 1). Department A reported the greatest number of crashes per year (mean = 356, sd = 24.1), followed by Department C (mean = 206.7, sd = 15.7) and B (mean = 62.3 sd = 2.5). Department B had the highest annual crash rate (mean = 15.8, sd = 1.3) per 10,000 service calls of the three departments (Table 1).

3.2. Main results

The Cumby-Huizinga test for autocorrelation showed there was significant autocorrelation in Department A (lag order 1), B (lag order 2) and C (lag order 7) crash rate time series, respectively.

Table 1
Profiles of fire departments participating in study.

	Department A	Department B	Department C
Primary Geography	Urban	Suburban	Suburban
Department Type	City, Career	County, Combo	County, Career
Population Served	>1,000,000	<500,000	>1,000,000
Area Size Served, sq. mi.	<500	<500	>2,000
Stations, n	>50	<50	>50
Personnel Size, n	>1,000	<1000	>1000
Fleet Size, n	>200	50–100	100–200
Emergency Calls, n	>400,000	>30,000	>200,000
Annual Crashes, mean (sd)*	356 (24.1)	62.3 (2.5)	206.7 (15.7)
Annual Crash Rate, mean (sd)*†	5.5 (0.5)	15.8 (1.3)	8.15 (0.8)
Number of Pre-RM Months Observed	28	27	29
Number of Post-RM Months Observed	23	24	22
Monthly Crash Rate Pre-RM, mean (sd)	6.5 (1.9)	14.6 (7.4)	8.2 (2.0)
Monthly Crash Rate Post-RM, mean (sd)	4.8 (1.1)	15.8 (7.0)	7.4 (2.2)

* 3-year average (2014–2016)
† per 10,000 emergency calls; Department A based on emergency run volume

These lags were specified in each department's Newey regression models to obtain unbiased standard errors.

The average monthly crash rate at Department A declined by approximately 26.1% (P < 0.001) from a mean of 6.53 per 10,000 calls during the pre-RM period to 4.82 during the post-RM period. Department A had a flat and non-significant crash rate trend prior to RM (β_1=-0.01, P = 0.79) (Fig. 1). Immediately post-RM, we observed a non-significant reduction in the overall crash rate level (β_2=-0.98, P = 0.30) of about 15.4%. Post-RM, we observed a non-significant reduction in the crash rate trend of −0.05 per month (P = 0.18) or about 1% per month (Table 2).

In Department B, the average monthly crash rate increased by 7.9% from 14.61 per 10,000 calls during the pre-RM period to 15.76 during the post-RM, but this was not statistically significant (P = 0.53). Department B showed a flat crash rate trend pre- and post-RM with no significant changes in the crash rate throughout the study period (Fig. 1). Immediately post-RM, we observed a statistically non-significant increase of 9.7% in the monthly crash rate (β_2=1.41, P = 0.70) (Table 2).

In Department C, the average monthly crash rate decreased by 10.1% (P = 0.19), from 8.24 per 10,000 calls during the pre-RM period to 7.40 during the post-RM period. There was a non-significant positive trend in the monthly crash rates prior to RM. (β_1=0.06, P = 0.16). Immediately post-RM, we observed a significant 28.4% reduction in their monthly crash rate (β_2=-2.65, P = 0.001); however, the post-RM trend did not differ from the pre-RM trend (β_3=-0.02, P = 0.73) and continued to increase by 0.08 crashes per 10,000 calls or 1.2% per month post-RM (Table 2).

Based on projections from the pre-RM crash trends, we estimated that the RM programs at Departments A and C contributed in part to a total of 167 and 121 crashes avoided, respectively (Table 3). In Department B, we observed an excess of 15 crashes more than expected.

3.3. Other analyses

In Department A, there was a non-significant upward trend in the Code 3 response crash rate prior to RM (β_1=0.06, P = 0.12). There was a 22.4% reduction in the monthly Code 3 response crash rate immediately post-RM, but the drop was not statistically significant (β_2=-0.90, P = 0.20) (Table 4). There was a significant change in the monthly Code 3 response crash rate trend post-RM (β_3=-0.11, P = 0.01) with an average monthly reduction in their Code 3 response crash rate of −0.06 per month (P < 0.001) or about 1.8% per month (Fig. 2). The average monthly Code 3 crash rate declined significantly by 24.18% from 3.0 per 10,000 calls pre-RM to 2.3 crashes post-RM (P = 0.04). Based on projections from the pre-RM crash trends, we estimated that we would have expected 602 Code 3 crashes in Department A during the post-RM period. Instead, we observed 295 Code 3 crashes for a total of 307 Code 3 crashes avoided during the post-RM period.

At the beginning of the study period, the monthly preventable crash rate at Department C was 3.21 crashes per 10,000 calls (Table 4). There was a significant upward trend in the preventable crash rate (β_1=0.06, P = 0.01) prior to the RM program. Immediately after the RM program, we observed a drop in the preventable crash rate by 25.2% (β_2=-1.11, P = 0.13), but the reduction was not statistically significant (Fig. 2). The post-RM preventable crash rate trend was relatively flat with no significant upward or downward change. There was a less than 1% reduction in the average monthly preventable crash rate from 4.07 per 10,000 calls to just 4.05 (P = 0.95). We estimated there would have been 288 expected preventable crashes in Department C during the post-RM period had the pre-RM trend continued. Instead, we observed 193 crashes for a total of 95 preventable crashes avoided during the post-RM period.

Department A's average annual ESVC repair costs (adjusted to 2018 dollars) by vehicle type are presented in Table 5. On average,

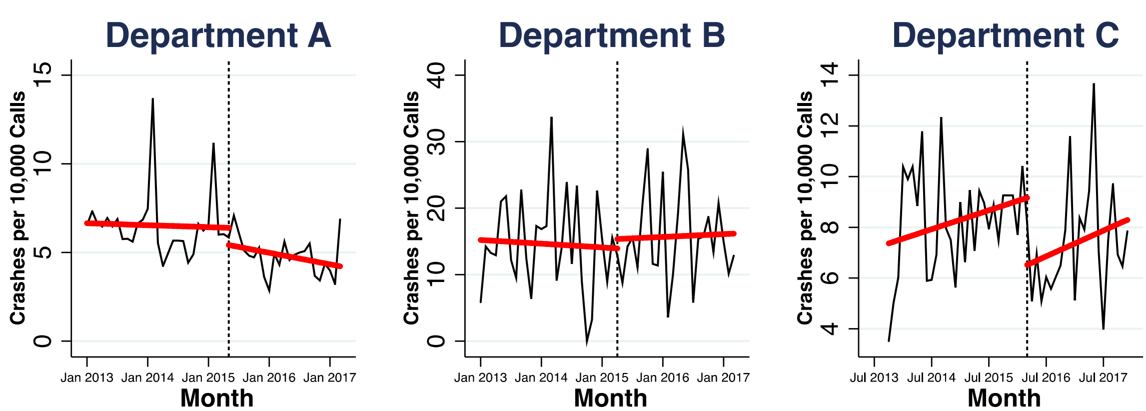

Fig. 1. Interrupted time series analysis results of change in crash rates (all crashes) at each department. The vertical dashed line indicates when the risk management intervention period began. The thin lines represent the actual observed crash rates over time. The thick straight lines represent the modeled mean trend in crash rates.

Table 2
Main results from segmented ordinary least–square regressions with Newey-West standard errors.

	Department A				Department B				Department C			
	All Crashes				**All Crashes**				**All Crashes**			
	β	**P**	**95% CI**		**β**	**P**	**95% CI**		**β**	**P**	**95% CI**	
Crash Rate at Beginning of Time Series (β_0)	6.65	<0.001	5.77	7.53	15.22	<0.001	11.03	19.41	7.37	<0.001	5.62	9.12
Average Monthly Change in Crash Rate Pre-RM (β_1)	−0.01	0.79	−0.08	0.06	−0.05	0.76	−0.36	0.26	0.06	0.16	−0.02	0.15
Immediate Change in Monthly Crash Rate Post-RM (β_2)	−0.98	0.30	−2.83	0.88	1.41	0.70	−5.76	8.57	−2.65	0.00	−4.14	−1.16
Average Monthly Change in Crash Rate Post-RM (β_3)	−0.05	0.40	−0.15	0.06	0.08	0.70	−0.34	0.51	0.02	0.73	−0.11	0.15
Linear Monthly Crash Trend Post-RM($\beta_1 + \beta_3$)	−0.05	0.18	−0.13	0.03	0.04	0.81	−0.26	0.33	0.08	0.09	−0.01	0.18

Table 3
A comparison of expected crashes during the post-risk management period, had the pre-risk management crash rate trends continued versus the actual number of crashes observed.

	Department A	Department B	Department C
Expected Crashes	781	108.8	474.7
Actual Crashes	614	124	353
Excess Crashes	−167	15.2	−121.7

crashes involving larger apparatus like aerials and ladders were the costliest per crash, followed by sport utility vehicles, pumpers and ambulances. The average cost per tort claim was about $2,850 (Table 5.).

The estimated number of crashes avoided in Department A was 167 with an average cost per ESVC avoided of $1,613 (in 2018 dollars). The estimated total cost savings due to crashes avoided was $269,411 (95%CI= $204,752 – $334,114) during the post-RM follow-up period. Alternatively put, repair costs declined 23.7% relative to pre-RM period.

4. Discussion

Our results show immediate reductions in overall crash rates post-RM in two of three fire departments (Department A and C) and a sustained downward trend in one department, though it was not statistically significant. Furthermore, emergency response crashes were reduced in the department implementing changes in Code 3 response policies, and preventable ESVCs were reduced in the department implementing increased drivers' training. We also provided data on economic savings associated with the RM program in one department that provided cost information. The results of these analyses demonstrate that a RM approach can be effective in reducing ESVCs in the U.S. fire service, although the benefits varied by fire department.

RM involves the adoption of a suite of interventions so it is generally not possible to identify the key intervention or mechanism that is responsible for observed changes in crash rates. However, some of the individual interventions chosen by our partner fire departments have been evaluated in other settings. Policies to reduce the use of lights and sirens during responses have been widely recommended and documented with generally positive results (Custalow & Gravitz, 2004; Wilbur, 2009; Williams, 2005). The Fire Department of the City of New York (FDNY) has revised response policies by reprioritizing emergency call types to identify emergencies that do not require Code 3 response (Wilbur, 2011). The resulting reduction in unnecessary Code 3 responses at FDNY was associated with a 32% reduction in overall crashes in their

Table 5
Average annual repair costs and tort claims costs due to ESVCs by vehicle type for Department A (2013 – 2014). Costs expressed in 2018 dollars.

Cost Category	N	Repair Cost Per Crash Mean($)
Vehicle Type		
Ambulances (e.g., Ford F350 XLT, F450)	184	1,029.76
Pumper Units (e.g., Spartan Gladiator)	86	1,088.83
Aerial or Ladders (e.g., Spartan, Pierce)	110	4,166.63
Sport Utility Vehicles (e.g., Ford Explorer, Expedition, F250)	54	2,630.20
Specialty Vehicles (e.g., Ford 750, Freightliner M2, etc.)	20	932.21
Tort Claims	82	2,850.14
Total Crash Cost (repairs and tort claims)	**454**	**1,613**

Table 4
Segmented ordinary least–square regression results with Newey-West standard errors for Code 3 crashes at Department A and Preventable crashes at Department C. Fifty-one months of observation.

	Department A Code 3 Crashes Only				Department C Preventable Crashes Only			
	β	P	95% CI		β	P	95% CI	
Crash Rate at Beginning of Time Series (β_0)	2.27	<0.001	1.37	3.17	3.21	<0.001	2.42	3.99
Average Monthly Change inCrash Rate Pre-RM (β_1)	0.06	0.12	−0.02	0.13	0.06	0.01	0.02	0.11
Immediate Change in Monthly Crash Rate Post-RM (β_2)	−0.90	0.20	−2.30	0.50	−1.11	0.13	−2.57	0.34
Average Monthly Change inCrash Rate Post-RM (β_3)	−0.11	0.01	−0.19	−0.03	−0.05	0.22	−0.12	0.03
Linear Monthly Crash TrendPost-RM ($\beta_1 + \beta_3$)	−0.06	<0.001	−0.08	−0.03	0.01	0.70	−0.06	0.09

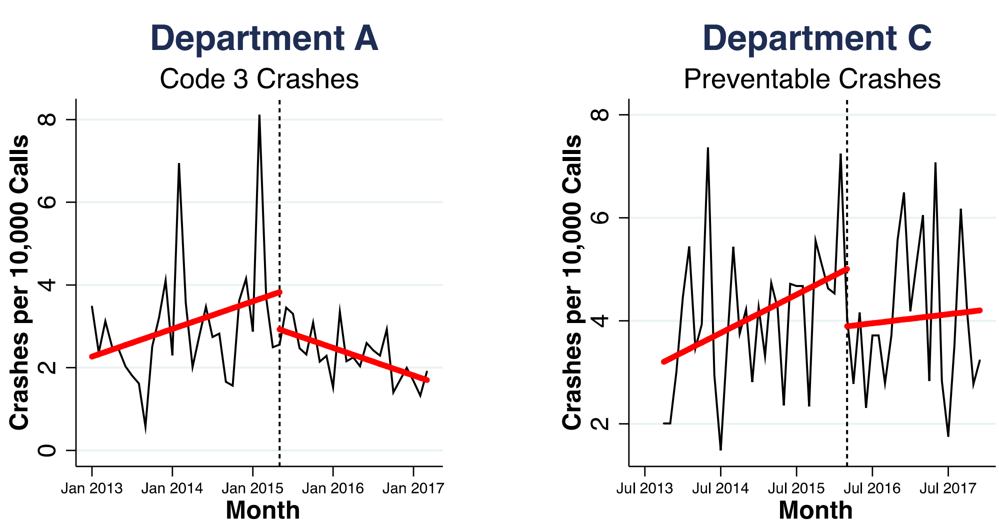

Fig. 2. Interrupted time series analysis results of changes in Code 3 crash rates in Department A and preventable crash rates in Department C. The vertical dashed line indicates when the risk management intervention period began. The thin lines represent the actual observed crash rates over time. The thick straight lines represent the modeled mean trend in crash rates.

department. Other departments that have reduced Code 3 responses have reported estimated over 75% reductions in overall crashes (Bui et al., 2018; Lindstrom, 2011). While timely response to emergencies is important, past studies have indicated that the association between response times and patient outcomes is unclear (Berger, 2010; Newgard et al., 2010). New simple triage algorithms have been developed to identify low priority emergency types to safely reduce the use of Code 3 responses by up to a third and can be used by other departments to begin reducing the use of Code 3 response (Isenberg, Cone, & Stiell, 2012). The sustained reduction in monthly Code 3 crashes in Department A suggests that policy-based interventions may have more sustained effects than other interventions, such as training.

Department B did not experience any significant changes to their overall crash rate. They rated animal collisions as a high priority risk and selected controls to reduce such collisions; however, animal collisions accounted for just 3% of all ESVCs at the department and were relatively rare albeit with high consequence and damage. Focus on these rare events may explain why we did not observe significant changes in their overall crash rate. The other interventions they chose to implement included providing standardized training for the operation of bay doors and placing telematics units on 12 vehicles. The initial telematics data reporting format was not considered useful, so drivers were not given their driving data to review. The drivers therefore may have not known they were being monitored, despite notices sent to them earlier in the study. This may have limited changes in driving behavior which otherwise may have occurred due to concern over being observed. This potential lack of knowledge of the study despite information being provided was reflected in another RM program to reduce injuries among firefighters, where Pollack et al. reported that up to 50% of surveyed firefighters in their study were not aware of implemented controls and up to 60% of those surveyed were not using implemented controls (Pollack et al., 2017).

The driver training at Department C resulted in a sharp reduction in crashes and non-preventable crashes immediately post-RM, but the positive post-trend suggests that the effects of the training program may have worn off over time and continued training may be necessary. In a recent literature review, it was found that fire departments that have implemented comprehensive classroom and hands-on drivers training programs significantly reduced their preventable and overall crash rates by up to 50% with durable and persistent reductions in crash rates over time (Bui et al., 2018). The most successful fire department driver training programs focused predominantly on field-based and hands-on training and required refresher training at regular intervals. This is in contrast to studies that have found novice and civilian driver education programs that focus on driving rules and laws to be largely ineffective in reducing crash risk (Ker et al., 2005; Ker, Roberts, Collier, Renton, & Bunn, 2003). Even the use of driving simulators, which have been used to augment the amount of hands-on driver training, has been found to be effective in improving driver safety and reducing crash risk in fire departments by over 30% in some cases (Lindsey & Barron, 2008; Raheb, 2005). The emphasis on field-based or hands-on driver training may be the key mechanism for improving driver safety and is indeed the best practice recommendation for occupational driver training programs (Network of Employers for Traffic Safety, 2016).

Previous research on the cost-effectiveness of risk management interventions in the fire service is limited. A risk management intervention focused on fitness training for new recruits resulted in a statistically significant reduction in injuries and workers' compensation claims, and a cost savings of nearly $33,000 in one year (Griffin et al., 2016). Similarly, risk management interventions in mining have been shown to be temporally associated with a reduction in injury and to have a positive return on investment (Griffin et al., 2018). Department A had a 23.7% reduction in repair costs relative to the pre-RM period. Large fire engines and aerial ladders accounted for the majority of total repair costs at Department A and reflected anecdotal reports from our fire department partners. In our discussions with Department A, they emphasized that turning-related crashes involving large aerial ladders and engines were very frequent because they sit on single frame chassis and are difficult to turn on narrow roads in dense urban settings. That challenge, combined with driver inexperience along streets where there is less turning radius, is one factor behind these crashes and costs.

Several challenges exist in cost attribution with this work. First, is obtaining itemized data with specific information from fire departments and local governments. For example, costs from out-of-court settlements were not readily available and could not be factored into the final estimate of crash costs at Department A. We found sites had accounting peculiarities that limited our ability to easily obtain itemized costs for more robust analyses. While the early cost evidence shows promise, a more comprehensive approach that accounts for specific details of property damage and medical expenses is needed to refine estimates. Without these other key cost categories factored in, the ESVC cost estimates provided from Department A should be considered conservative.

There are some limitations to this study. RM typically involves continuous cycles of risk assessment and new interventions (International Organization for Standardization, 2009). As the RM programs applied in this study did not continue beyond one cycle, the estimates of effects are likely underestimations of the true effect of a RM program applied with fidelity. While interrupted time series analysis controls for temporal effects and trends, our analysis does not rule out that the observed changes to crashes may have been due to unmeasured exogenous factors (e.g., random variability) independent of the RM program. Our cost analysis was performed for only one site and assumes that the total difference in expected versus actual crashes were attributable to the RM program. In reality, it is unlikely that all reductions in crashes were attributable to the RM program and a proportion of reductions in crashes may be attributable to other unmeasured factors. Finally, although our time series analysis was based on 51 months of observations, our analysis may have been underpowered to detect the effect sizes of RM programs, resulting in multiple non-significant results. While studies have suggested that 24 or more time points is sufficient for 80% power to detect moderate effect sizes (Zhang, Wagner, & Ross-Degnan, 2011), our observed effect sizes may have been too small and underpowered.

5. Conclusions

Proactive RM is a useful strategy used in a variety of industries to reduce occupational risks and hazards. Prior research has shown that RM may be readily adopted by fire departments and is generally perceived to be an amenable and useful process, and our current results show that RM can be effective in reducing ESVCs in the fire service. Results in one department suggest a gross economic savings but more research is needed to understand the full economic implication of investment in RM and the financial return it may offer cities and municipalities.

6. Declarations

6.1. Availability of data and materials

The data collected from this study were from administrative crash reports and apparatus repair costs from the participating departments. De-identified data can be made available from the corresponding author upon reasonable request and written approval from department partners.

7. Competing interests

The declare that they have no competing interests.

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